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Research article

Explaining Mean Relative Regression (MRR) as Measurement for Risk in Investment Project Appraisal

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Abstract

Regression analysis is not known to feature within the ambit of project investment appraisal mainly due to the univariate nature of the cash flows employed which is a major divergence from the usual outcome and predictor(s) bi or multivariate analysis involved in normal regressions. This study uses a variant of the regression analysis which converts a univariate data set to a bivariate regression using the population mean as a pivot. Mean Relative Regression (MRR) has been used with many variations and diverse interpretations. This study distinguishes, explains, and introduces the application of MRR to investment projects' proposal analysis. Six sample projects were analyzed using the Discounted Cash Flow (DCF) technique and further evaluated for risk of non-realization the MRR. The findings showed that the risk levels outlined by the MRR which were also validated with a t-test at the 95% confidence level revealed a well-ordered project viability ranking in consonance with the projects' break-even points or Internal Rate of Return (IRR). The paper recommends the inclusion of MRR in investment projects' appraisal to facilitate project risk prediction and appropriate risk inclusion into project appraisal discounting rate.

Introduction

Matters of research in the accounting and finance discipline have so far dwelt on comparisons of regulatory frameworks, sustainability, economic performance, and testing compliance of firms with rules and economic regulations. They have nonetheless relegated matters of scientific innovations concerning their roles into the background. Investment appraisal of capital project initiation is one area needing such innovations. The futuristic nature of capital project investments makes the decision to invest or not to be unduly fraught with the dangers of either failure or under-realization of the objectives of the project. The Discounted Cash Flow (DCF) technique was introduced to take into consideration the aspect of perennial devaluation of money in an economy. Uncertainty, which could come about due to climatic, political, economic, demographic, and technological volatility, in addition to the ever-evolving consumer behavior giving rise to risk, was not adequately considered under the DCF analytical scenario.

Risk is an aspect of economic life designed to cover the vagaries of uncertainty in future economic projects. In capital investment decisions, failing to recognize or appropriately incorporate risk can lead to systematic overestimation of project viability. Many corporate failures and abandoned projects can be traced to inadequate risk assessment or the use of models that obscure rather than illuminate the true distribution of possible outcomes.

Study Justification

Although probability theory and statistical tools offer mechanisms for quantifying risk, their practical application varies widely in complexity and interpretability. There are many other attempts at quantifying and integrating risk into investment project planning. Such approaches ranged from Risk-Adjusted Discount Rates (RADR) and Certainty Equivalent Adjustments (CEA) to Scenario Analysis and Monte Carlo simulation. Many of these remain mathematically demanding, computationally intensive, or difficult to interpret. Monte Carlo simulation, for example, is widely praised for its ability to incorporate stochastic variability, yet its effective use requires assumptions about probability distributions and a level of statistical literacy that could be difficult to comprehend by many enthusiasts. Regression analysis was also included as another means of estimating risk in [1] and further buttressed by [2] with the use of quantile regression and kernel estimation. Other regression model usage concentrated mainly on evaluating forecasting accuracy and assessing predictive models [3,4]; none has considered its use for measuring risk in investment appraisals.

Study objectives

This paper intends to explore other aspects of the regression analysis, specifically Mean Relative Regression (MRR), that might offer an easier method of regression-associated risk estimation technique that could be readily understood by non-experts in mathematical analysis. The paper will consider two areas in regression that could offer clues on risk:

a. the quality and curve of linearity of the data being regressed
b. the coefficient of correlation of the x and y variables.

Literature review

Regression analysis remains a central tool in statistical modeling and empirical research. Its theoretical foundations in least squares estimation and statistical inference provide a rigorous basis for understanding relationships among variables. With extensions to generalized linear models and regularized techniques, regression continues to evolve in response to modern data challenges. While powerful, its validity depends on careful adherence to assumptions, appropriate model specification, and thoughtful interpretation. Proper application ensures meaningful and reliable insights across scientific disciplines [5-7].

Regression analysis is a foundational statistical methodology used to model, estimate, and infer relationships between a dependent variable and one or more independent variables. It is widely applied across disciplines including economics, psychology, epidemiology, engineering, and the social sciences to examine associations, test hypotheses, and generate predictions. By quantifying the direction and magnitude of relationships among variables, regression analysis provides a rigorous framework for both explanatory and predictive modeling.

Conceptual Foundations of Regression Analysis

Regression analysis examines how a response variable changes as a function of one or more predictor variables. The general linear regression model is expressed as:

$$yi = \beta 0 + \beta 1xi + \varepsilon i \qquad (1)$$

where y_i represents the dependent variable for observation i, β_0 is the intercept, β_1 is the regression coefficient, and εi is the stochastic error term capturing unexplained variation [8]. The coefficients represent the expected change in y_i for a one-unit increase in the corresponding x_i, holding other variables constant.

The method of Ordinary Least Squares (OLS) is commonly used to estimate the parameters. OLS minimizes the sum of squared residuals:

$$S(\beta) = (y - X\beta)'(y - X\beta) \qquad (2)$$

where S(ß) denotes the predicted value [7]. Under the Gauss-Markov assumptions, OLS estimators are the Best Linear Unbiased Estimators (BLUE), meaning they have the smallest variance among all linear unbiased estimators [5].

Assumptions of Linear Regression

The validity of regression inference depends on several key assumptions, amongst which are linearity, independence, homoscedasticity, normality of errors, and no perfect multicollinearity among the predictors.

Model Type	Dependent Variable Type	Key Feature	Example Application
Simple Linear Regression	Continuous	One predictor	Effect of study hours on test scores
Multiple Linear Regression	Continuous	Multiple predictors	Wage determination models
Logistic Regression	Binary	Logit link function	Disease presence/absence
Poisson Regression	Count	Log link, count data	Number of accidents
Ridge and Lasso Regression	Continuous	Regularization	High-dimensional prediction
Nonlinear	Continuous	Nonlinear	Pharmacokinetic
Regression		functional form	modeling

Violations of these assumptions can lead to biased, inefficient, or inconsistent estimates

(Wooldridge, 2020) [8]. Diagnostic tools such as residual plots, Variance Inflation Factors (VIF), and formal tests (e.g., the Breusch-Pagan test for heteroscedasticity) are used to assess these conditions [7]. Violations of these assumptions can lead to biased, inefficient, or inconsistent estimates [8-14]. Diagnostic tools such as residual plots, Variance Inflation Factors (VIF), and formal tests (e.g., the Breusch-Pagan test for heteroscedasticity) are used to assess these conditions [7].

Types of Regression Models

Regression analysis encompasses a wide array of models beyond simple linear regression.

Logistic regression models the log-odds of a binary outcome using the probability of an event occurring [15]. Regularization methods such as ridge and lasso regression address overfitting and multicollinearity by adding penalty terms to the loss function [9].

Estimation, Inference, and Model Evaluation

Regression analysis facilitates statistical inference through hypothesis testing and confidence intervals. A typical hypothesis test evaluates whether one or more regression coefficients differ significantly from specified values, using a t-statistic:

$$t = [\hat{\beta}j - \beta j,0]/\sqrt{\hat{V}ar}(\hat{\beta}j) \qquad (3)$$

Where:

$$Va\hat{r}(\hat{\beta}j) = \hat{\sigma}^2[(X'X)^{-1}]_{j_j} \qquad (4)$$

And:

$$\hat{\sigma}^2 = (\hat{\epsilon}'\hat{\epsilon})/(n-k) \qquad (5)$$

where n is the number of observations, k is the number of estimated parameters, and ∈ˆis the vector of OLS residuals [5].

Model fit is often assessed using the coefficient of determination (R or R^2), being the proportion of variance explained by the model, and could be adjusted for the number of predictors. While the model complexity could be penalized using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) with Root Mean Squared Error (RMSE) measuring the model predictive accuracy. Also, cross-validation techniques are increasingly used in predictive modeling to assess out-of-sample performance [9].

Applications Across Disciplines

Regression analysis has extensive applications in almost every discipline especially in economics, medicine, psychology, engineering, accounting and finance, and machine learning.

Its versatility stems from its adaptability to various data structures and research questions.

Limitations and Challenges

Despite its strengths, regression analysis faces several challenges, which include omitted variable bias, which occurs when relevant predictors are excluded, leading to biased coefficient estimates.

Endogeneity, which arises when explanatory variables correlate with the error term.

Multicollinearity, which has been observed to inflate standard errors and reduce interpretability. Improper design of a regression model can result in overfitting, which compromises result generalization in complex models. Regression analysis identifies associations between variables, not necessarily causal relationships leading to causality limitations.

However, advanced techniques such as instrumental variables, fixed effects models, and causal inference frameworks attempt to address these concerns [8].

Risk Prediction in Discounted Cash Flow situation

Given that a normal regression analysis involves at least two variables-one outcome and one or more predictors-it becomes a dilemma in project analysis with Discounted Cash Flow (DCF), which provides only one variable in the form of a stream of cash flows made up of initial outflows and the consequent inflows, leaving the analyst the arduous task of sourcing the complementary variable. This is the area where many researchers experimented with inferences from quantile regression and kernel estimator [10,1,2].

Other researchers also experimented with what they termed Mean Relative Regression. [11] stated that Mean Relative Regression is not a standard, widely-used named method in econometrics or statistics, but in context it almost always refers to regression or model evaluation built on relative (percentage-type) errors rather than absolute level errors. In practice, this shows up in two closely related ideas - mean relative error as a regression loss which uses Mean Relative Error (MRE) as the objective instead of Mean Squared Error (MSE). With this, the error is measured as a proportion of the actual value; and relative-error-based regression estimators.

Mean Relative Regression quantifies the average relative difference between predicted and observed values. It is conceptually similar to Mean Relative Error (MRE) or Mean Absolute Percentage Error (MAPE) but is often applied in regression contexts where model residuals are analyzed relative to the magnitude of the true values. Mean Relative Regression quantifies the average relative difference between predicted and observed values. It is conceptually similar to Mean Relative Error (MRE) or Mean Absolute Percentage Error (MAPE) but is often applied in regression contexts where model residuals are analyzed relative to the magnitude of the true values [12,13].

In a typical regression, we minimize the Mean Squared Error (MSE). In Mean Relative Regression, the loss function is adjusted to account for the magnitude of the actual value (y_i) [12].

Mean Relative Regression (MRR) is a statistical and machine learning concept used to evaluate model performance by comparing predicted and actual values in a relative sense. It is particularly useful in contexts where absolute errors are less informative than proportional or relative deviations, such as economics, environmental modeling, and forecasting applications [6].

Definition and Concept

Mean Relative Regression quantifies the average relative difference between predicted and observed values. It is conceptually similar to Mean Relative Error (MRE) or Mean Absolute Percentage Error (MAPE) but is often applied in regression contexts where model residuals are analyzed relative to the magnitude of the true values [6].

The general formula for Mean Relative Regression is:

The general formula for Mean Relative Regression (MRR) complementary data is:

$$\text{MRR complementary data} = (y - \hat{y})/y \qquad (6)$$

While the objective function to obtain the full loss content (L) is given as:

$$L = n - 1\sum^{n}_{i=1} \left| yi - yi^{-\hat{y}i} \right| \qquad (7)$$

where:
y = actual (true) value
$\hat{y}$ = predicted value
n = number of observations

This measure expresses the mean of the relative differences between predicted and observed values, providing a scale-independent metric that allows comparison across datasets with different magnitudes.

Interpretation

When computed MRR is 0, it indicates a perfect prediction (no relative error). But higher MRR values indicate greater average relative deviation between predictions and actuals. However, MRR can become unstable when actual values (y) approach zero, leading to inflated relative errors. For this reason, some studies use modified versions such as Symmetric Mean Absolute Percentage Error (sMAPE) or Mean Absolute Scaled Error (MASE).

Applications

Mean Relative Regression has been applied in fields such as: Econometrics for evaluating forecasting accuracy of macroeconomic indicators [3]; Energy and Environmental Modeling for assessing predictive models for emissions or energy consumption [4]; and Machine Learning for comparing regression models in cross-validation frameworks [6].

In a nutshell, Mean Relative Regression provides a normalized, interpretable measure of model performance that captures proportional prediction errors. It is a valuable complement to absolute error metrics, especially when comparing models across varying scales or units. However, care must be taken when actual values approach zero, as this can distort relative error measures.

Extracting Risk Metrics from Regression Analysis

To extract the risk metric from the regression analysis, we look at the direction of the coefficient of determination, otherwise referred to as the R^2. The R^2 summarizes how well a regression model explains the variation in the dependent variable. It measures the proportion of total variability in the outcome that is accounted for by the explanatory variables included in the model. In classical linear regression, R^2 provides a goodness-of-fit measure with higher values indicating that the fitted model explains a larger share of the observed variation in the dependent variable [7] and can be interpreted as the fraction of the sample variance of y explained by the regression [5]. The R^2 is measured as:

$$R^2 = ESS/TSS \qquad (8)$$

Where:

$$ESS = \sum^n t = 1(\hat{y}i - \bar{Y})^2 \qquad (9)$$

$$ESS = \sum^n t = 1(yi - \bar{Y})^2 \qquad (10)$$

Given that R^2 represents the proportion of the predictor(s) or x that can be found responsible for y, the outcome, then it is safe to conclude that 1 - R^2 is the proportion outside the influence of x. Recognizing the fact that the cash flow stream of a project is the predictor (x) which value y was yet to be established, it follows that the coefficient of determination of the stream represents the chance of success of the project given that the ability of the project analysis to attain a higher R^2 value is the same as stating that the projected cash flow stream will influence a larger share of the observed variation in the Net Present Value (NPV) of the project [16]. Leaving the risk of not attaining a positive NPV at 1 - R^2.

Materials and Methods

This study adopts a desk-research and comparative literature review approach to design a new mean relative regression model that can incorporate investment risk measurement into the regression analysis, drawing on cash-flow estimates from six proposed projects previously evaluated by the lead author.

The DCF framework was used to determine baseline project viability, while the standard deviation and co-variation techniques were applied in conjunction with the MRR to compare and quantify the risk expected in the projected cash flows. The R^2 computed which was the basis for the generation of the MRR risk was tested for statistical significance using the t distribution hypothesis testing model at the 95% confidence level, where $t = [r\sqrt{(n-2)}] / \sqrt{(1-r^2)}$, and p value = 2P (T > t).

Model formulation

The following notations are used throughout the analysis:

m = mean cash flow
a_t = annual cash flow for time t.
p_t = probability of cash flow (a_t) occurring
ha = highest annual cash flow
$\hat{a}_t = \hat{y}$ = predicted annual cash flow for time t.
mrr_risk = Mean relative regression risk
ESS = explained sum of squares
TSS = total sum of squares
e = residual
t = time or cash flow period

With MRR, the annual cash flow projections which becomes the predictor variable will be regressed against the outcome variable computed using the formula for m, â, with the associated risk computed using the ESS and TSS as follows:

$$m = (\sum^n t a_t)/n \quad (11)$$

$$\hat{a}_t = a_t(a_t/m) \quad (12)$$

$$R^2 = ESS/TSS \quad (13)$$

$$mrr\_risk = 1 - R^2 = RSS/TSS \quad (14)$$

$$RSS = \sum^n t = 1(y_i - \hat{y})^2 \quad (15)$$

$$CV = \sigma/m \quad (16)$$

where:
σ is the standard deviation of the cash-flow distribution. **ha** is the highest cash flow value. **la** is the lowest cash flow value.
m is the mean cash flow.

Study Hypotheses

To test the significance of the relationship between the predicted cash flows and the projected cash flows for the sample projects used for the analysis and the significance of the risks produced by the Mean Relative Regression on each project, we hypothesize as follows:

$H_0$1: There is no significant relationship between the predicted cash flows and the projected cash flows for the sampled projects.
$H_0$2: The associated risks as computed with the Mean Relative Regression for the sampled projects are not significant enough to induce project failure.

Computational Tool

The MRR analyses were Performed Using Valustats (VSP) version 2.0, which supports iterative simulation, regression modeling, and statistical diagnostics.

Data and Analysis

This section presents the empirical data used in the comparative appraisal of the six sampled projects and applies the two risk-assessment techniques-Mean-Relative Regression (MRR), and the statistical coefficient of variation.

Computational Procedures

The cash flow data were analyzed using ValuStats (VSP) version 2.0 statistical package which converted the cash flows to their predictive complements using equation 12 as listed earlier to regress each of the projects' cash flow streams to produce the MRR risk metrics. Then followed by the DCF analysis which produced the Net Present Value (NPV) and the Internal Rate of Returns and (IRR). ValuStats (VSP) 2.0 was also used to compute the projects' coefficient of variations.

Table 1: Cash-Flow Listing and Descriptive Statistics for Six Projects.

Cash Flow (Yr)	Project 1	Project 2	Project 3	Project 4	Project 5	Project 6
1	45000	2000	3000	2500	55	22000
2	45000	2000	3000	2500	55	22000
3	45000	3000	3500	2500	55	34000
4	50000	3000	3500	3000	155	34000
5	50000	3000	3500	3000	155	47500
6	50000	4000	3500	3000	155	47500
7	55000	4000	4000	3500	255	58000
8	55000	4000	4000	3500	255	58000
9	55000	4000	4000	3500	355	68500
10	55000	4000	4000	3500	355	68500
11	55000	5000	4000	3500	455	79000
12	55000	5000	4000	3500	455	79000
13	60000	5000	4000	3500	555	92000
14	60000	5000	4000	4200	555	92000
15	60000	5000	4500	4200	655	102000
16	60000	6000	4500	4200	655	102000
17	60000	6000	4500	4200	755	112000
18	65000	6000	4500	5500	855	112000
19	65000	6000	5000	5500	955	120000
20	65000	6000	5000	5500	955	120000
Outflow	200000	20000	20000	15000	1000	200000
NPV	119179.11	1711.99	2665.34	4622.95	492.84	117239.17
IRR	22.85	16.46	17.44	19.68	19.69	21.17
Mean	55500	4400	4000	3715	435	73500
Std. Dev	6,305	1,280.63	547.72	916.12	289.25	31,595.89
Co-Var	11.36%	29.11%	13.69%	24.66%	69.12%	42.99%
Mrr_Risk	0.34%	13.98%	13.06%	17.88%	21.86%	10.86%
R	0.9966	0.8602	0.8694	0.8212	0.7814	0.8914
R-Squared	0.9932	0.7399	0.7559	0.6744	0.6106	0.7946
T. Stat (R)	51.2747	7.15648	7.46572	6.1058	5.31265	8.344655
P value (R)	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
T Stat Risk	0.01443	0.599	0.558875	0.771	0.95043	0.46349
P value Risk	0.88526	0.54917	0.57625	0.44071	0.34289	0.64301

The Coefficient of Variation (CV) provides a normalized measure of dispersion, enabling comparison across projects with different cash-flow magnitudes. The MRR on the other hand provides a smoothed measure of spread of the projects' predicted cash flows as alternatives to the cash flow values projected by the project initiators. This is where the strength of the MRR lies.

Table 2: Comparison of MRR smoothed Cash Flows and Initiators Cash Flows.

Project	Type	Lowest Value	Highest Value
P1	MRR Smoothed	36,486.50	76,126.12
	Projected Cash Flow	45,000.00	65,000.00
P2	MRR Smoothed	909.09	8,181.82
	Projected Cash Flow	2,000.00	6,000.00
P3	MRR Smoothed	2,250.00	6,250.00
	Projected Cash Flow	3,000.00	5,000.00
P4	MRR Smoothed	1,682.37	8,142.67
	Projected Cash Flow	2,500.00	5,500.00
P5	MRR Smoothed	6.95	2,096.61
	Projected Cash Flow	55.00	955.00
P6	MRR Smoothed	6,585.03	195,918.37
	Projected Cash Flow	22,000.00	120,000.00

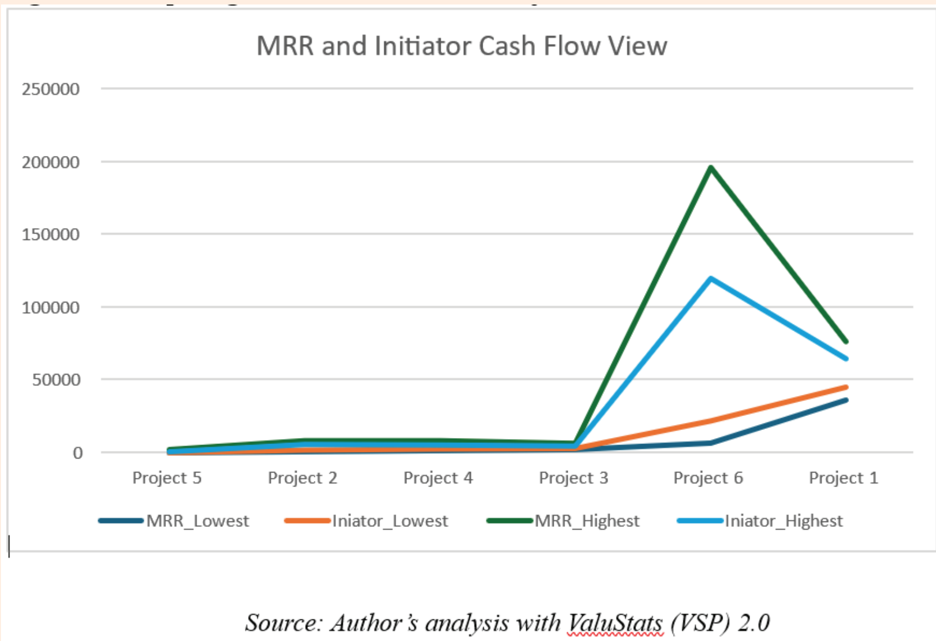

Figure 1: Comparing MRR Cash Flow with Projected Cash Flow.

Discussion of Findings

Table 1 laid down the results of the data analysis. Project 5 exhibits the highest coefficient of variation (69.12%) statistical variance analysis, indicating substantial volatility relative to its mean cash flow. The MRR on the other hand, showed a somewhat more realistic risk figures judging from the NPV performance of the six projects, however, it was observed that the both the coefficient of variation and the MRR risk metrics ranked the projects in the same order, except for projects two and six.

From the look of the risk figures, the MRR risk seemed more realistic because while co-variation method considers more of the ability of the cash flows to reach the highest point or degenerate to the lowest projection, the MRR considered both loss of money value, the effluxion of time, and the ability to match costs with the expected cash flow revenue.

Again, comparing the co-variation and the MRR metrics, we shall attempt to explain the difference in outcomes between the two as follows:

a. Though the results indicated differences in metrics, they nevertheless follow the same order in performance ranking.
b. Coefficient of variation being a product of the standard deviation is greatly influenced by its value which is determined by the absolute dispersion of the data around the mean. Given the usual presence of outliers in a data stream like cash flows, the values of standard deviations must expectedly be large and so must consequently influence the size of the coefficient of variation.
c. The computed MRR predictive values have been smoothed by the process of regressing and the way the y values were generated (noting that the initiators projected cash flow figures were used to represent the x variable figures.

Table 2 replicated in graphical form as Figure 1 displays the curves for the lowest and highest possible cash flow figures under the normal projection and the MRR smoothed stream. It can be observed that the MRR predicted cash flows curves are either below the projected cash flows at the lower rung or above them at upper level indicating that the smoothed values followed a well-ordered mathematical manipulations, thus showing that the limitations imposed by the standard deviation estimations can be exceeded even above or below the project initiators projections.

The order of the project ranking followed the same pattern with the MRR risk when the coefficient of determination 'R' and its t-test values are considered. The best outcome from the whole analysis is that all the t-test values for the relationship between the predicted cash flows and the projected cash flows were significant at the 95% confidence (or 5% significant) level, while the test of effects of the risks computed were shown to be insignificant. Implying that, though the risks of not meeting the highest projected cash flows might exist, they are not strong enough to affect the realization of any of the projects. These results indicate that the two null hypotheses ($H_0$1 and $H_0$2) are rejected for failure of proof. This is a further indication of the effectiveness of MRR measurement metric.

The essence of measuring risk in project investment appraisal is to know the extent to which reliance can be placed on the viability of proposed projects on one hand and the extent to which the risks can be mitigated in the other hand. Due to its futuristic nature, most risks associated with investment are buoyed mainly on cash flow realization which is primarily dependent on the future value of money. The process of discounting which was instituted as a corrective measure against the diminishing value of money occasioned by the effluxion of time and using the most appropriate discounting factor remains the most reliable key to the solution [17]. The generation of a risk metric on a proposed project is a precaution attempt to guide against project failure by adjusting for the risk factor in the cash flow discounting rate. However, the extent to which the risk metric can be incorporated into the discounting rate will be limited to the value that can be accommodated between the project's discounting base rate and the project's break-even rate known as the Internal Rate of Return (IRR).

Therefore, using the computed MRR risks, we adjust for the risks in the projects as in Table3 following:

Table 3: Risk Adjustments

Project	Base Rate	Risk	IRR	Risk Absorbed	Risk-adjusted Rate	% of Risk Absorbed
Project 1	15	0.34	22.85	0.34	15.34	100
Project 2	15	13.98	16.46	1.46	16.46	10.44
Project 3	15	13.06	17.44	2.44	17.44	18.68
Project 4	15	17.88	19.68	4.68	19.68	26.17
Project 5	15	21.86	19.69	4.69	19.69	21.45
Project 6	15	10.86	21.17	6.17	21.17	56.81

From Table 3, Project 1 continues to exhibit the profile of the most viable of all the six projects as it is the only one that fully absorbed its risk element into the discount factor and still stayed below the IRR. Another interesting aspect to observe is that the risk absorption ratio also changed the order of viability of projects 4 and 5.

Conclusion

Effective recognition and integration of risk are indispensable components of investment planning, project appraisal, and project execution. Ignoring risk in capital-investment decisions is analogous to navigating an aircraft without a compass-possible, but dangerously uninformed. Equally problematic is the use of inappropriate or misleading risk metrics. As [5] cautioned, flawed risk measures can misguide investors into accepting projects that should be rejected or abandoning opportunities that are fundamentally sound [18]. This study demonstrates that the concept of Mean-Relative Regression (MRR) offers a credible alternative to project risk analysis which neither require high technical expertise nor advanced computational resources that may not be readily available to average practitioners. As reviewed from extant literature, Mean Relative Regression (MRR) has many variants, purposes, and interpretations. However, in this paper, the MRR was used to model and analyze the inherent risk in future investment projects for the purpose of adjusting them in the projects' discount factors as a safeguard for project investment decision makers. Thus, demonstrating that MRR is not only used to study the flow of regression data errors around the mean trend but it can also be used to model risks in monotone data structure such as project cash flows. The findings of this study reinforce the argument that simplified, well-structured risk-integration frameworks can produce decision-useful results comparable to more complex models. By enabling managers to quantify risk using regression analysis, and incorporate the risk meaningfully into investment appraisal, such models enhance the reliability of capital-budgeting decisions and support more resilient strategic planning and promotes a meaningful intercourse between pure science and management science ideologues.

Declarations

Ethical Approval and Consent to Participate

This research did not involve any human or animal subjects. The study exclusively utilized available investment cash flow projections used for tutorial purposes only.

According to the Babcock University Research and Ethics Committee (BUREC) guidelines, research using tutorial archived documents is exempt from ethical scrutiny that applies to studies involving direct contact with humans or animals.

References

1. Huang AY (2012) Value at risk estimation by quantile regression and kernel estimator.
2. He Y, Hou Y, Peng L, Shen H (2020) Inference for conditional value-at-risk of a predictive regression. The Annals of Statistics 48(6): 3442-3464.
3. Theil H (1966) Applied economic forecasting. North-Holland Publishing Company.
4. Willmott CJ, Matsuura K (2005) Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in assessing average model performance. Climate Research 30(1): 79-82.
5. Dixit AK, Pindyck RS (1994) Investment under uncertainty. Princeton University Press Greene, WH. (2018). Econometric analysis (8th ed.,). Pearson.
6. Hyndman RJ, Koehler AB (2006) Another look at measures of forecast accuracy. International Journal of Forecasting 22(4): 679-688.
7. Montgomery DC, Peck EA, Vining GG (2021) Introduction to linear regression analysis (6th ed.). Wiley.
8. Wooldridge J M (2020) Introductory econometrics: A modern approach (7th ed.). Cengage Learning.
9. James G, Witten D, Hastie T, Tibshirani R (2021) An introduction to statistical learning: With applications in R (2nd ed.). Springer.
10. Guikema SD, Goffelt JP (2008) A flexible count data regression model for risk analysis. Risk Analysis 28(1): 213-223.
11. Nikolopoulou K (2003) Regression to the mean/definition & Examples. Scribbr.
12. Jones MC, Park H, Shin KI, Vines SK, Jeong SO (2008) Relative error prediction via kernel regression smoothers. Journal of Statistical Planning and Inference 138(9): 2887-2898.
13. Kozak A, Kozak RA (1995) Notes on regression through the origin. The Forestry Chronicle 71(3): 326-330.
14. Armstrong JS, Collopy F (1992) Error measures for generalizing about forecasting methods: Empirical comparisons. International Journal of Forecasting 8(1): 69-80.
15. Hosmer DW, Lemeshow S, Sturdivant RX (2013) Applied logistic regression (3rd ed.). Wiley.
16. Review of Quantitative Finance and Accounting, 41, 225-251.
17. Ostermann T, Willich SN, Lüdtke (2008) Regression toward the mean-A detection method for unknown population mean based on Mee and Chua's algorithm, BMC Medical Research Methodology 8(52).
18. Skouras S (2001) The sign of a mean regression: Characterization, estimation, and applications. ssrn.com.